

# **Local Weighting–Based Diagnostics for Bayesian Poststratification**

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# Are US non-voters becoming more Republican?

## Blue Rose research says yes:

“Politically disengaged voters have become much more Republican, And because less-engaged voters swung away from [Democrats], an expanded electorate meant a more Republican electorate.”

[Blue Rose Research, 2024] (On Ezra Klein show, major professional pollsters)

## On Data and Democracy says no:

“Claims of a decisive pro-Republican shift among the overall non-voting population are not supported by the most reliable, large-scale post-election data currently available.”

[Bonica et al., 2025] (Berkeley professor co-author, major professional researchers)

- 
- The problem is very hard (it's difficult to accurately poll non-voters)
  - Different data sources
  - **Very different statistical methods:** ★
    - Blue Rose uses Bayesian hierarchical modeling (MrP)
    - The CES uses weighted averages (calibration weighting)

## Our contribution

We provide a calibration weighting interpretation of MrP analyses that:

- Is easily computable from MCMC draws and standard software, and
- Defines MrP versions of key diagnostics that motivate calibration weighting.

We provide apples-to-apples comparisons between MrP and calibration weighting.

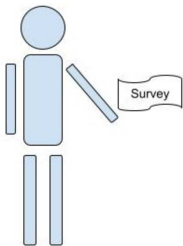
- Introduce the statistical problem and two methods (calibration weighting and MrP)
- Describe one of the classical calibration weighting diagnostics (covariate balance)
- Define MrPaw & state a key theorem
- Real-world results
- Future directions

# The basic problem

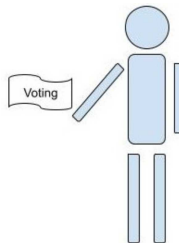
We have a survey population, for whom we observe:

- Covariates  $\mathbf{x}$  (e.g. race, gender, zip code, age, education level)
- Responses  $y$  (e.g. A binary response to “do you support policy such-and-such”)

We want the average response in a target population, in which we observe only covariates.



Observe  $(\mathbf{x}_s, y_s)$  for  $s = 1, \dots, S$



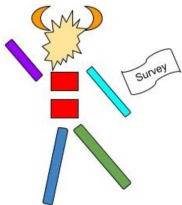
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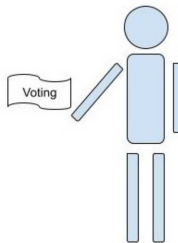
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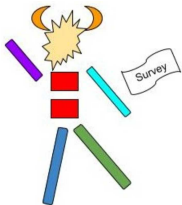
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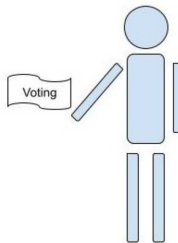
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**The problem is that the populations are very different.**

Our survey results may be biased.

How can we use the covariates to say something about the target responses?

## Two approaches

We want  $\mu := \frac{1}{T} \sum_{t=1}^T y_t$ , but don't observe target population  $y_t$ .

- Assume  $p(y|\mathbf{x})$  is the same in both populations,
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← (We open this box, providing analogues  
of all these diagnostics)

# What are we weighting for?<sup>1</sup>

We want:

$$\text{Target average response} = \frac{1}{T} \sum_{t=1}^T y_p \approx \frac{1}{S} \sum_{s=1}^S w_s y_s = \text{Weighted survey average response}$$

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You can check covariate balance for any calibration weighting estimator.

Even more, covariate balance is the criterion for a popular class of calibration weight estimators:

## Raking calibration weights

“Raking” selects weights that

- Are as “close as possible” to some reference weights
- Under the constraint that they balance some selected regressors.

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## Generalized covariate balance checks

We want to balance  $f(\mathbf{x})$  because we think  $\mathbb{E}[y|\mathbf{x}]$  might plausibly vary  $\propto f(\mathbf{x})$ , and want to check whether our estimator can capture this variability.

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## Generalized covariate balance (GCB) (informal)

Pick a small  $\delta$ , and define a *new response variable*  $\tilde{y}$  such that

$$\mathbb{E}[\tilde{y}|\mathbf{x}] = \mathbb{E}[y|\mathbf{x}] + \delta f(\mathbf{x}).$$

We know the change this is supposed to induce in the target population.

Covariate balance checks whether our estimators produce the same change.

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Then, check whether your estimator  $\hat{\mu}(\cdot)$  produces the same change:

$$\underbrace{\hat{\mu}(\tilde{y}) - \hat{\mu}(y)}_{\substack{\text{Replace weighted averages} \\ \text{with changes in an estimator}}} \stackrel{\text{check}}{=} \delta \frac{1}{T} \sum_{t=1}^T f(\mathbf{x}_p).$$

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When  $\hat{\mu}(\cdot) = \hat{\mu}_{\text{CAL}}(\cdot)$ , GCB recovers the standard covariate balance check.

**Step one:** Construct  $\tilde{y}$  such that  $\mathbb{E} [\tilde{y}|\mathbf{x}] = \mathbb{E} [y|\mathbf{x}] + \delta f(\mathbf{x})$ .

## Generalized covariate balance for MrP

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Two possibilities:

- Allow  $\tilde{y}$  to take values other than  $\{0, 1\}$  and set  $\tilde{y} = y + \delta f(\mathbf{x})$ , or
- Use an estimate of  $\mathbb{E} [y|\mathbf{x}]$  to draw new binary  $\tilde{y}$ .

We define theory and methods for the first, and provide tools for generating data using the second method for potentially problematic regressors.

## Generalized covariate balance for MrP

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## Taylor series

Form the approximation

$$\hat{\mu}_{\text{MRP}}(\tilde{y}) = \sum_{s=1}^S w_s^{\text{MRP}} (\tilde{y}_s - y_s) + \text{Residual} \quad \text{where} \quad w_s^{\text{MRP}} := \frac{d}{dy_s} \hat{\mu}_{\text{MRP}}(y).$$

If MrP were linear (e.g. if you use OLS instead of hierarchical logistic regression), then

- The residual is zero,
- $\hat{\mu}_{\text{MRP}}(y) = \sum_{s=1}^S w_s^{\text{MRP}} y_s$ , and so
- $\hat{\mu}_{\text{MRP}}(\tilde{y})$  is a calibration weighting estimator, and  $w_s^{\text{MRP}}$  are its weights. (Cite Gelman)

In general, MrP is truly nonlinear. The residual is only small when  $\tilde{y} \approx y$  (i.e., when  $\delta \ll 1$ ).

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It happens that the needed derivatives are given by simple a posteriori covariances involving only the inverse link function  $m(\mathbf{x}; \theta)$  and log likelihood [Giordano et al., 2018].

These can be computed using standard MCMC software (e.g. Bürkner [2017]).

## Theorem

- Let  $\tilde{y} = y + \delta f(\mathbf{x})$ ,
- $\hat{\mu}_{\text{MRP}}$  be a hierarchical logistic regression posterior expectation, and
- $\mathcal{F}$  be a Donsker class of uniformly bounded functions on  $\mathbf{x}$ .

Then, with probability approaching one, as  $N \rightarrow \infty$ ,

$$\sup_{f \in \mathcal{F}} \left( \hat{\mu}_{\text{MRP}}(\tilde{y}) - \left( \hat{\mu}_{\text{MRP}}(y) + \sum_{s=1}^S w_s^{\text{MRP}} \delta f(\mathbf{x}_s) \right) \right) = O(\delta^2) \quad \text{as } \delta \rightarrow 0$$

The supremum over  $\mathcal{F}$  is the primary technical contribution! It means we are justified in searching over regressors to find imbalance.

Draws on our prior work on uniform and finite-sample error bounds for Bernstein–von Mises theorem–like results [Giordano and Broderick, 2024, Kasprzak et al., 2025].

Analysis of changing names after marriage (based on Alexander [2019])

- **Target population:** ACS survey of US population 2017–2022 [Ruggles et al., 2024])
- **Survey population:** Marital Name Change Survey [Cohen, 2019]
- **Respose:** Did the female partner keep their name after marriage?
- For regressors, use bins of age, education, state, and decade married.

Survey observations:  $S = 4,364$

Target observations (rows):  $T = 4,085,282$

Uncorrected survey mean:  $\frac{1}{S} \sum_{s=1}^S y_n = 0.462$

Raking:  $\hat{\mu}_{\text{CAL}} = 0.263$

MrP:  $\hat{\mu}_{\text{MRP}} = 0.288$  (Post. sd = 0.0169)

# Figure

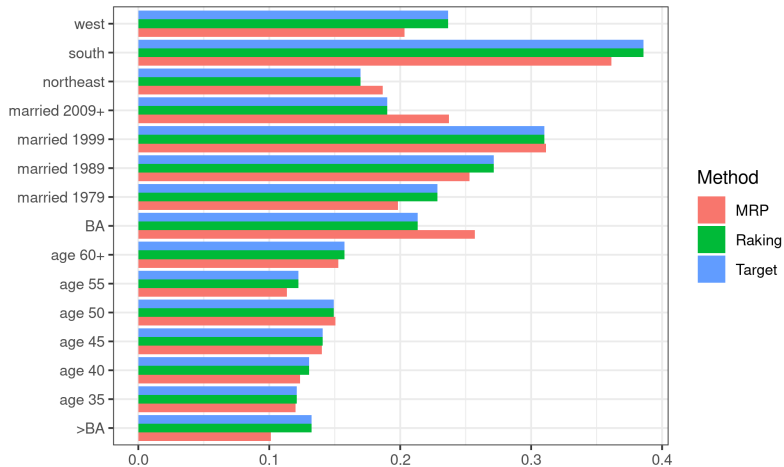


Figure 1: Imbalance plot for primary effects

# Figure

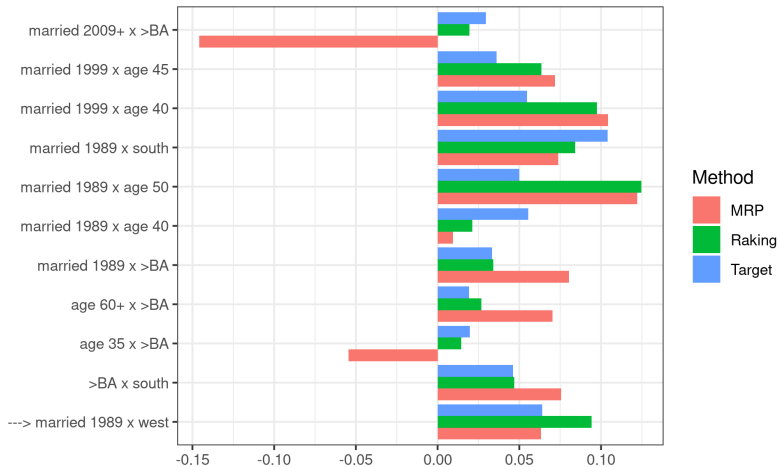
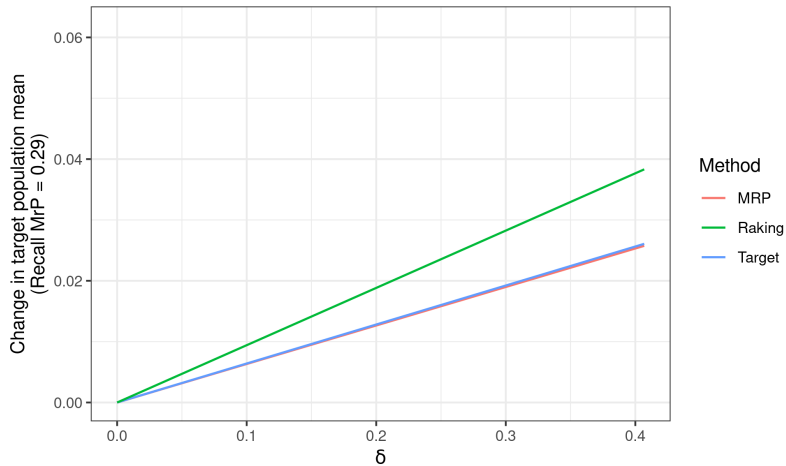
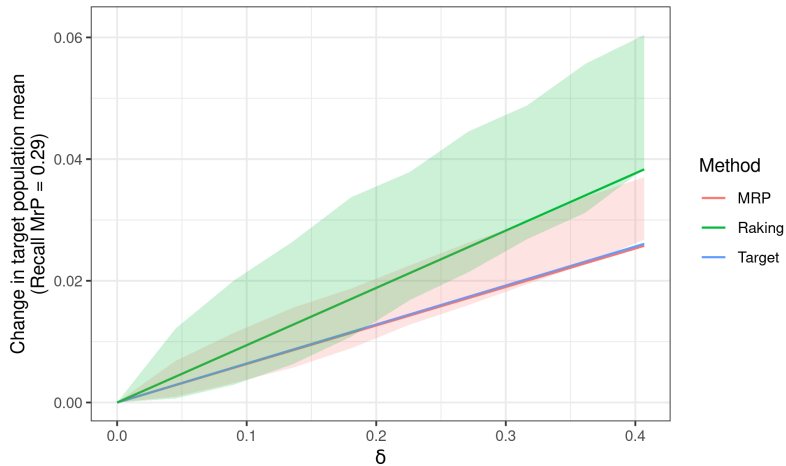


Figure 2: Imbalance plot for select interaction effects



**Figure 3:** Continuous predictions Alexander

## Figure



**Figure 4:** Continuous predictions Alexander



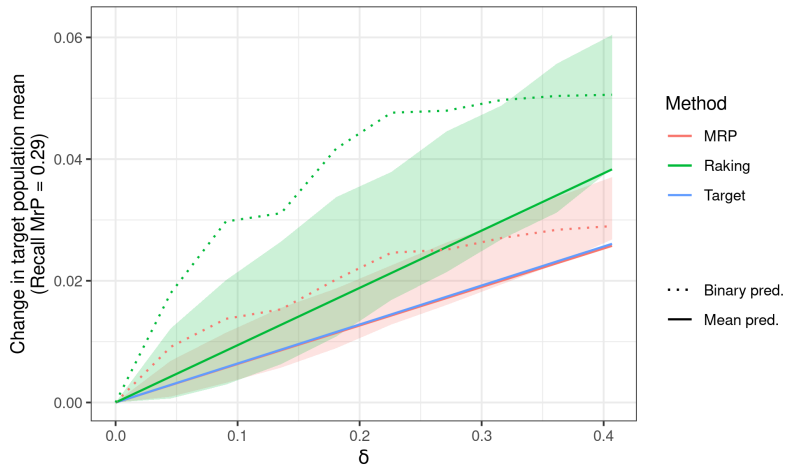
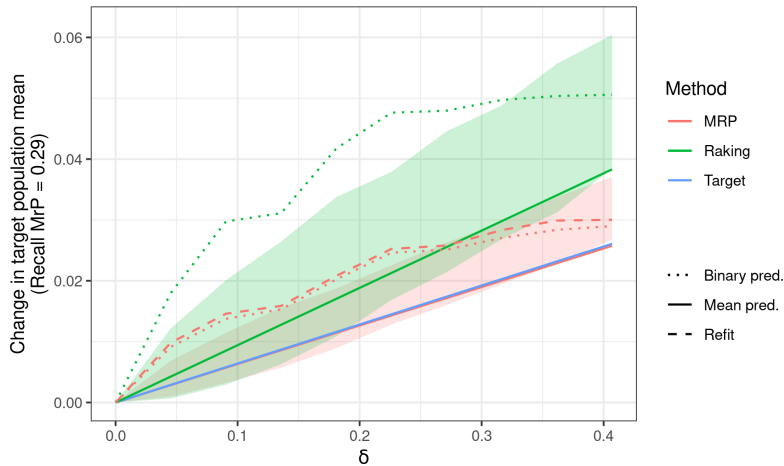


Figure 5: Continuous predictions Alexander

# Figure



**Figure 6:** Continuous predictions Alexander

- Instance of a very general class of local consistency checks that generalize classical regression checks (work with Sequoia)
- Versions for GLMMs (work with Vladimir)
- Going beyond classical Bayesian sensitivity (work with Lucas)

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